Deutsche Forschungsgemeinschaft

Connect Sensors to Perception via Semantic Streams

SmartEdge

11th Linked Data in Architecture and Construction Workshop
Matera, 15th, June, 2023

AIoTwin

Danh Le-Phuoc, DFG Principle Investigator and BIFOLD Junior Fellow

BIFOLD

Fraunhofer FOKUS

Me and my work

- Co-editor of W3C/OGC standard Semantic Sensor Network Ontology

  https://www.w3.org/TR/vocab-ssn/

- Developed one of the first RDF/Semantic Stream Processing Frameworks, **CQELS** (Continuous Query Evaluation over Linked Stream) → *(Semantic) Stream Reasoning*

- Principle Investigator of the DFG project, **COSMO** (Computing Foundations for Semantic Stream Processing) → *Performance and Scalability*

- *Technical Coordinator of EU Horizon project, **SMARTEDGE** (*Semantic Low-code Tools for Edge Intelligence*)* → *Sensor fusion for Autonomous Vehicles, V2X and Robotics*

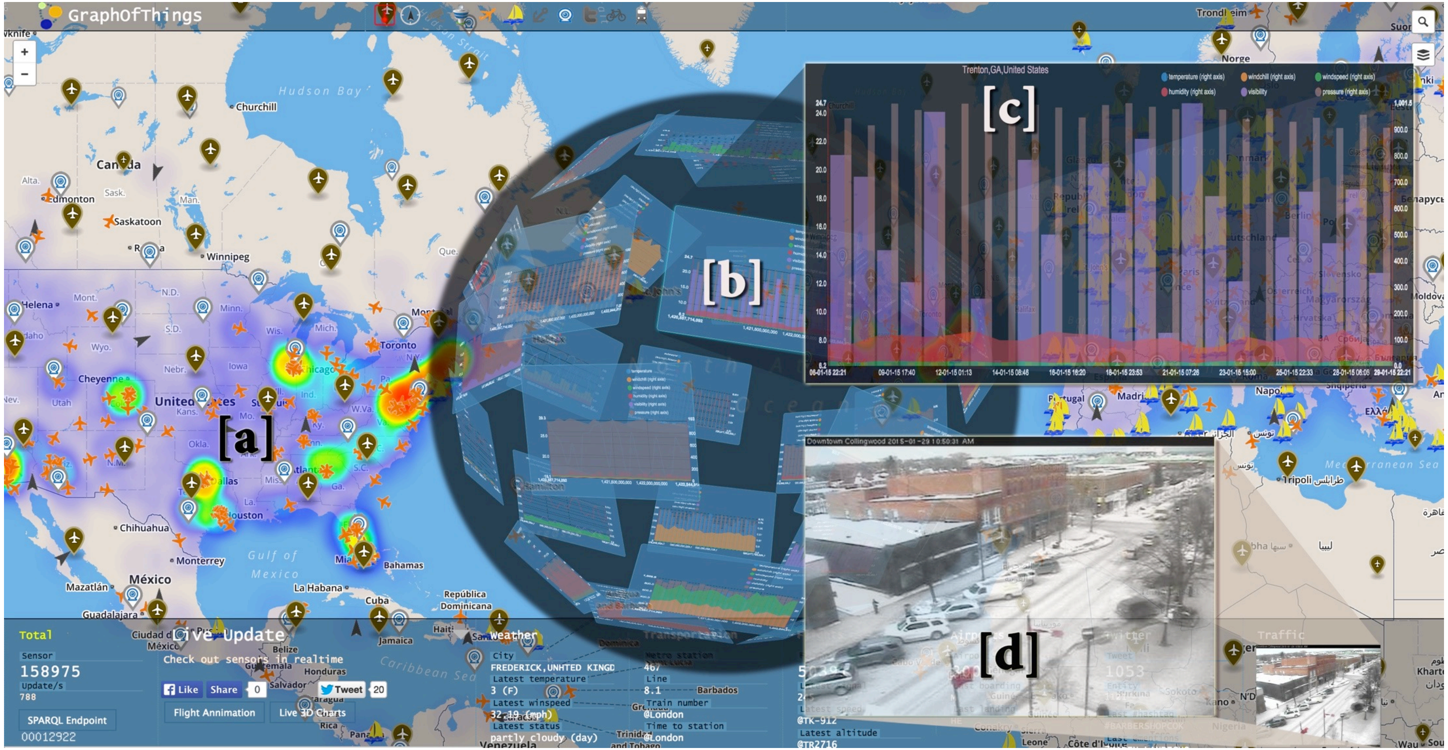
- BIFOLD Junior Fellow and Project Lead of the Berlin Institute for Foundations of Learning and Data (bifold.berlin) → *Neural-Symbolic AI for Cooperative Perception in V2X*

- **Connect Sensors to Stream Graphs**
- Program Semantic-based Perception
- Emerging Applications
- Integrate Spatial Knowledge into Perception

Connect Sensors to the Graph of Things

(Semantic, Spatial and Temporal correlation)

http://graphofthings.org/: >200K live stream sources, >200 billion RDF triples/ graph edges

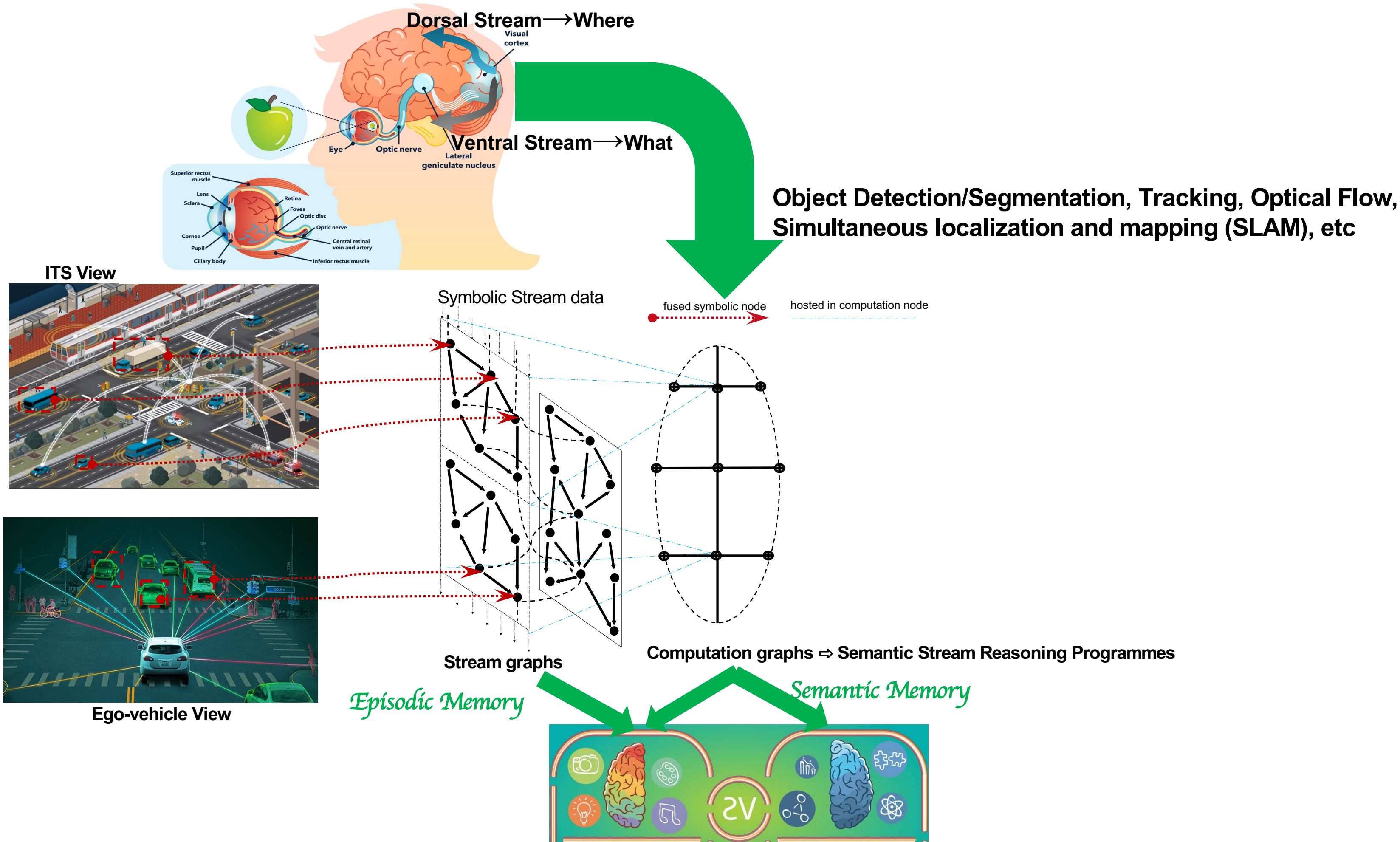


Le-Phuoc D. et al. The Graph of Things: A step towards the Live Knowledge Graph of connected things. J. Web Semantics 2016
Le-Phuoc D. et al. Live linked open sensor database. iSemantics 2010

Synergies from Cognitive Neuroscience

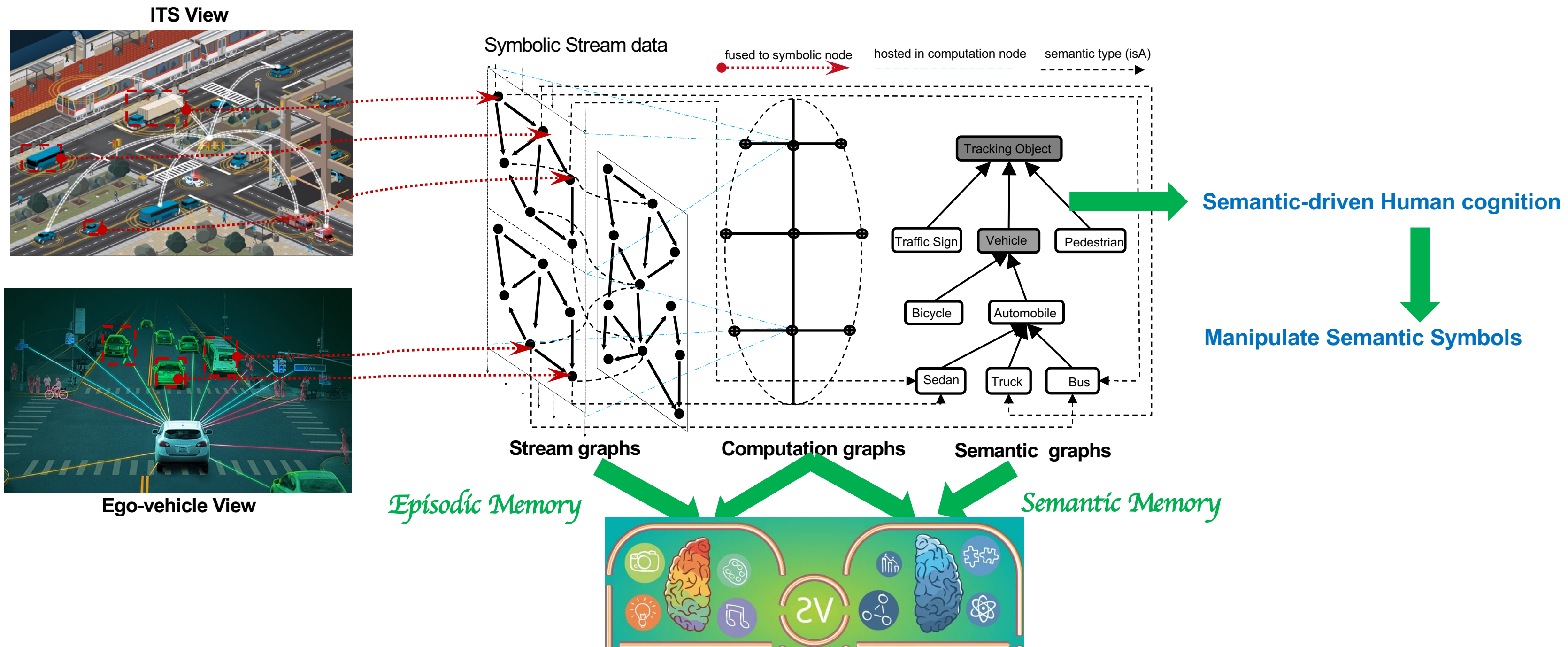
- ➢ Endel Tulving. 1972. *Episodic and semantic memory*. In Organization of Memory, ed. E Tulving, W Donaldson, pp. 381–403. New York: Academic
  - ❖ **Semantic memory** is organized knowledge a person possesses about *words* and other *verbal symbols*, their *meanings and referents*, about the relations among them, and about rules, *formulas*, and *algorithms for the manipulation of these symbols, concepts and relations* ⇨ **Semantic Knowledge Graphs?**
  - ❖ **Episodic memory** is associated with the *events* that take place in the life of an individual. It receives and store information about *temporally dated episodes* or *events* and temporal spatial relations among these events⇨ **Event/Stream/(Spatial-)Temporal Graphs?**
- ➢ Many studies of Cognitive Neuroscience shown *interdependence* in terms of *encoding and retrieval* ⇨ **Composability + Reasoning?**

Semantic Memory and Episodic Memory as Semantic Streams

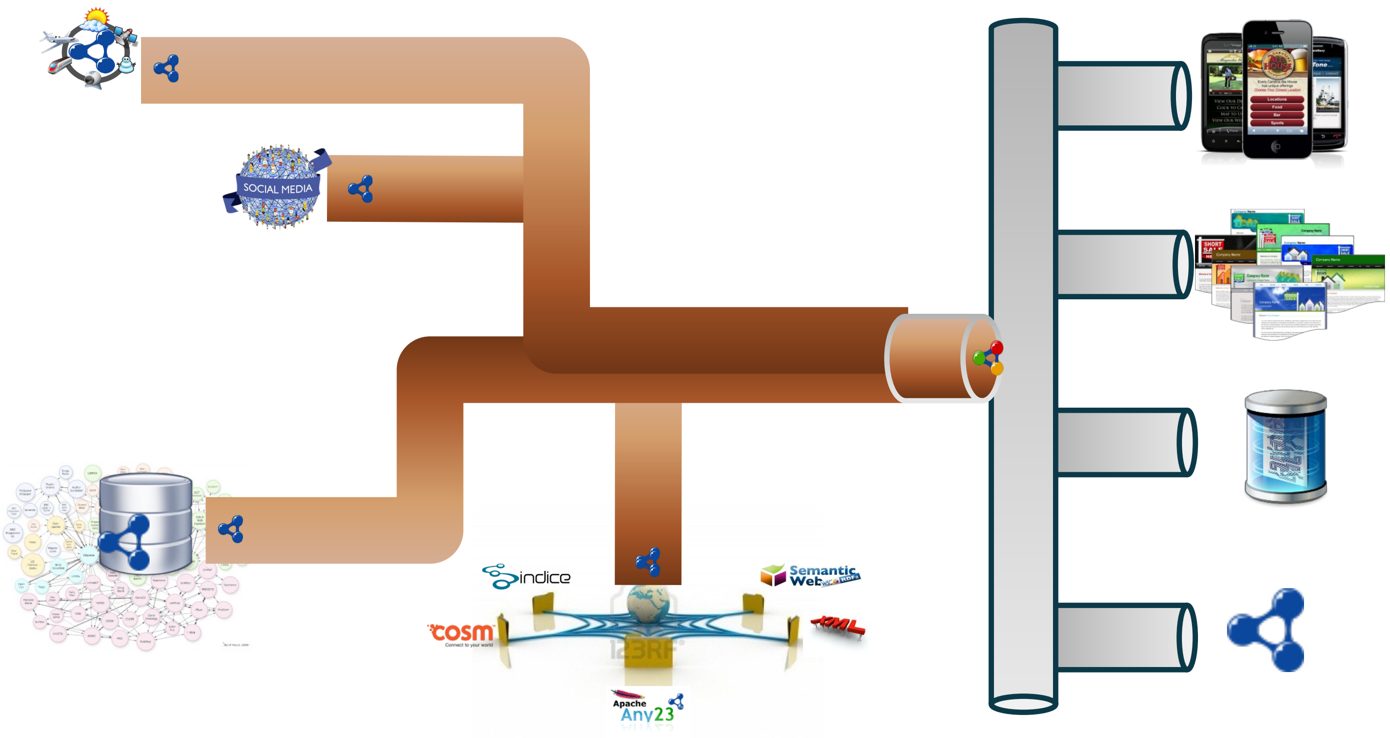


Semantic Streams: Computation model of Semantic Memory and Episodic Memory

Le-Phuoc, D., Hauswirth, M. (2022). Semantic Stream Processing and Reasoning. In: Zomaya, A., Taheri, J., Sakr, S. (eds) Encyclopedia of Big Data Technologies.



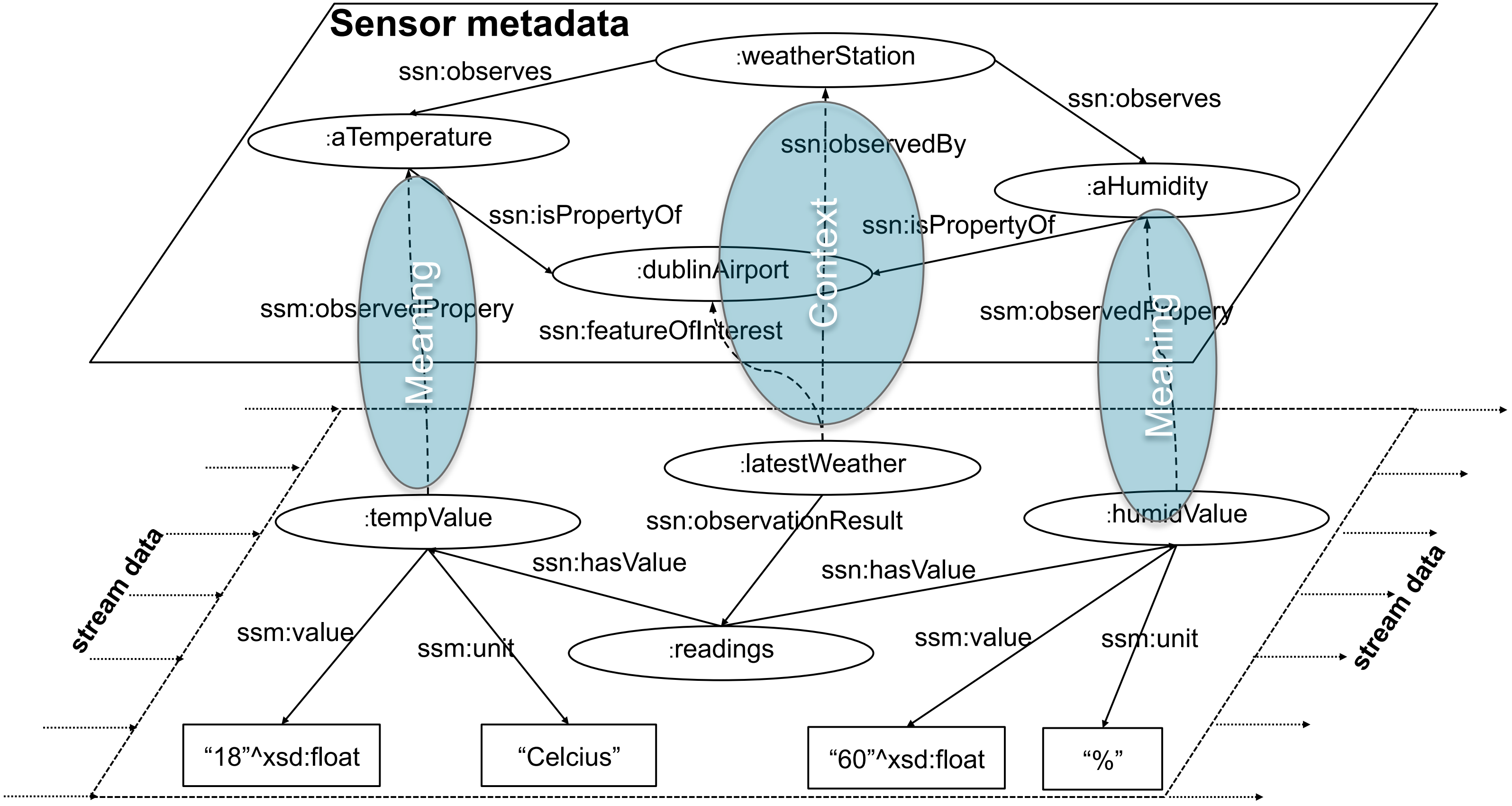
Unified Data Integration Bus with Semantic Streams in RDF Graphs



Bröring A…Le-Phuoc D. et al. Enabling IoT Ecosystems through Platform Interoperability. IEEE Softw. 34(1), 2017

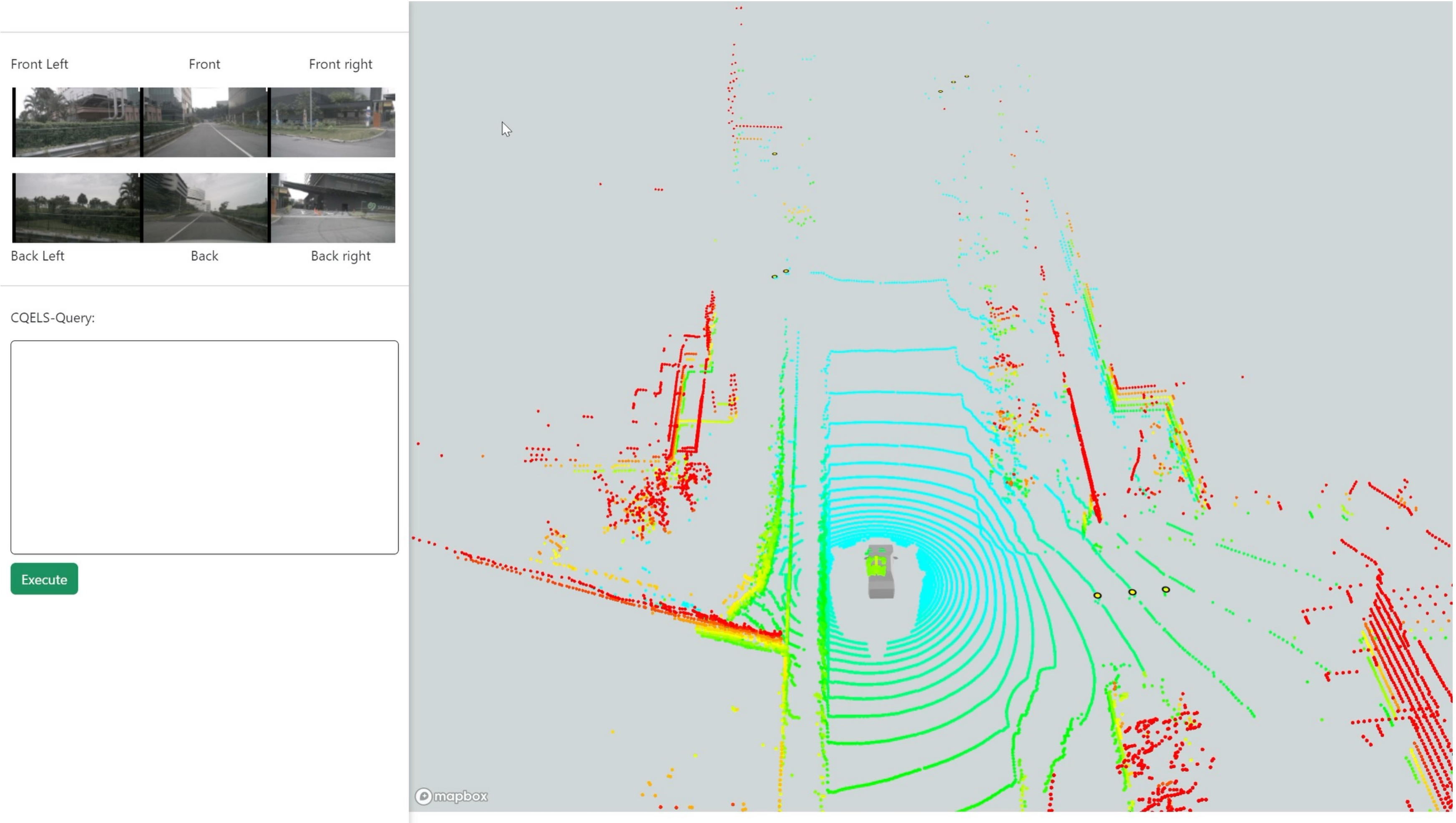
Le-Phuoc D. et al. Rapid prototyping of semantic mash-ups through semantic web pipes, WWW 2009

Stream of Sensory Observations as Stream Graphs

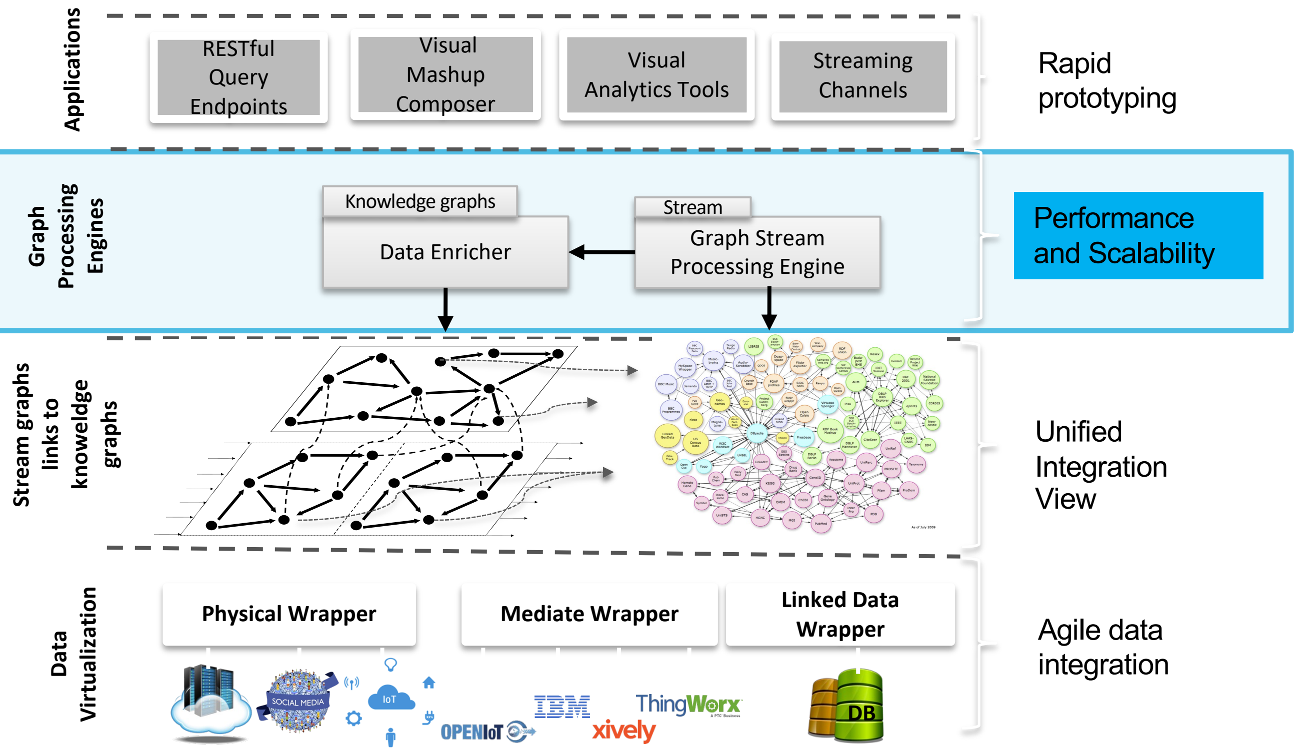


W3C/OGC Semantic Sensor Network ontology

Semantic Streams ⇨ Semantic-driven Declarative Programming



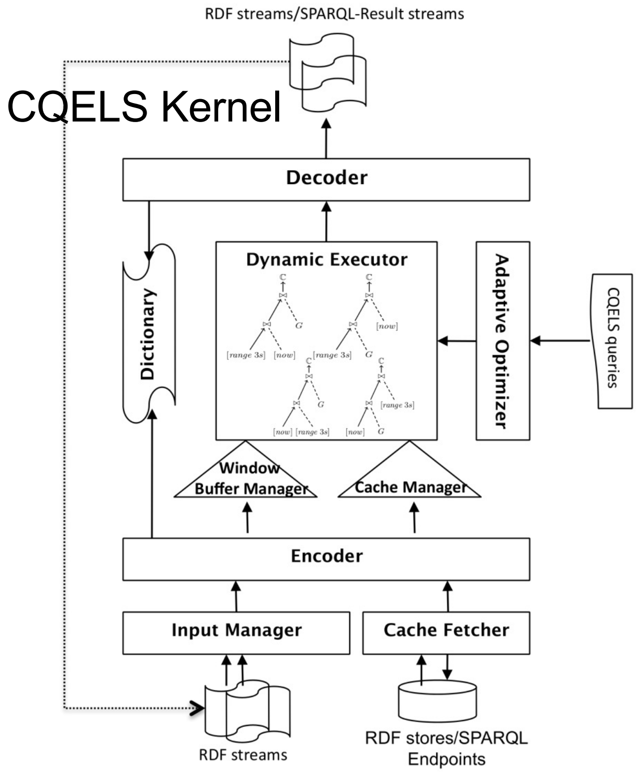
Unified Framework Using Processing Stream Graphs as Middleware



Anh L.T, .. Le-Phuoc D...et al. Towards Building Live Open Scientific Knowledge Graphs. WWW Companion 2022.
Nguyen M. D, .. Le-Phuoc D..Towards autonomous semantic stream fusion for distributed video streams. DEBS 2021.
Le-Phuoc D.. et al. A middleware framework for scalable management of linked streams. J. Web Semantics, Nov, 2012

CQELS execution Framework:

Autonomous RDF/Graph Stream Processing Kernel



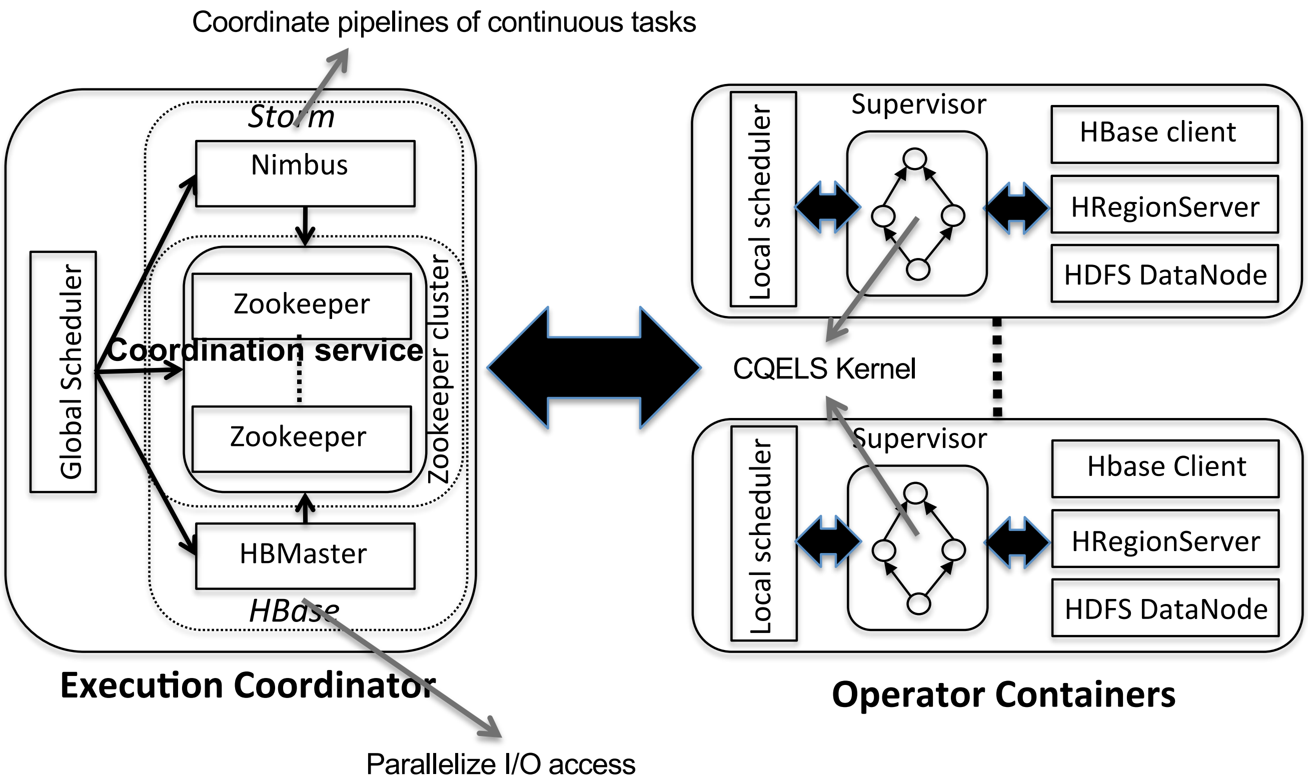
100-1000 time faster than Relational or RDF engines

Four key improvements:

- Native storage structure for stream graphs
- Operator-aware indexing scheme
- Adaptive optimization
- Incremental Evaluation

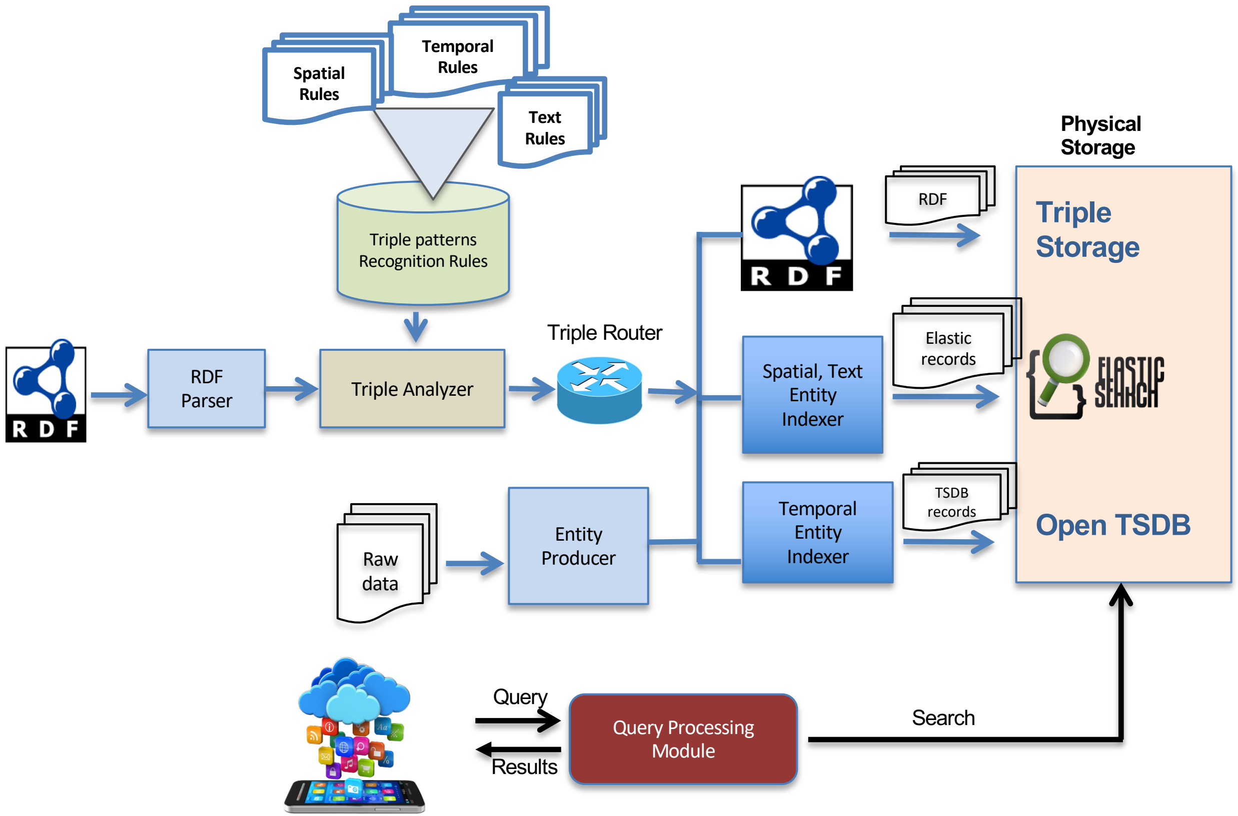
Manh N.D,.. Le-Phuoc D.. Autonomous RDF Stream Processing for IoT Edge Devices. JIST 2019
Le-Phuoc D.. et al. Operator-aware Approach for Boosting Performance in Processing RDF streams. J. Web Semantics 2017
Le-Phuoc D. et al. A Native and Adaptive Approach for Unified Processing of Linked Streams and Linked Data. ISWC 2011

Scaling Up: Scalable and Elastic Data Processing Framework



Le-Phuoc D.. et al. Elastic and scalable processing of linked stream data in the cloud. ISWC 2013

Scaling Out: Spatial, Temporal and Semantic-based Partitioning



Hoan N.M.Q … Le-Phuoc D. EAGLE - A Scalable Query Processing Engine for Linked Sensor Data. Sensors 19(20), 2019
Hoan N.M.Q … Le-Phuoc D. A learning approach for query planning on spatio-temporal IoT data. IOT 2018,
Hoan N.M.Q and Le-Phuoc D. An elastic and scalable spatiotemporal query processing for linked sensor data. Semantics' 2015

- Connect Sensors to Stream Graphs
- **Program Semantic-based Perception**
- Emerging Applications
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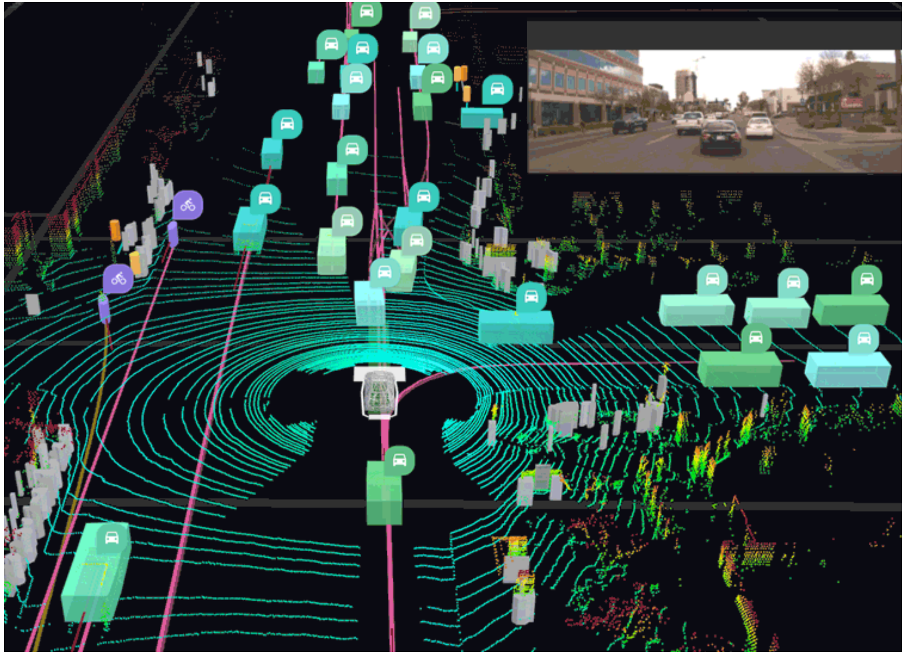
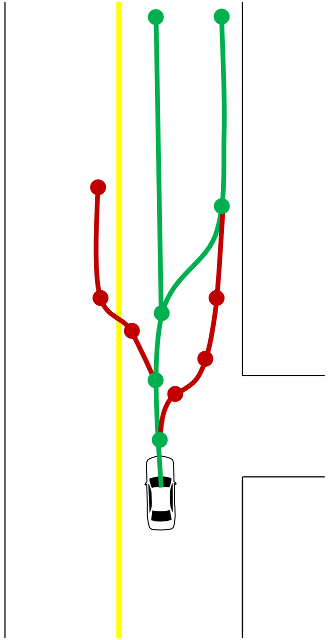
Declarative Programing for Multimodal Sensor Fusion



Sensor data at different formats and modalities

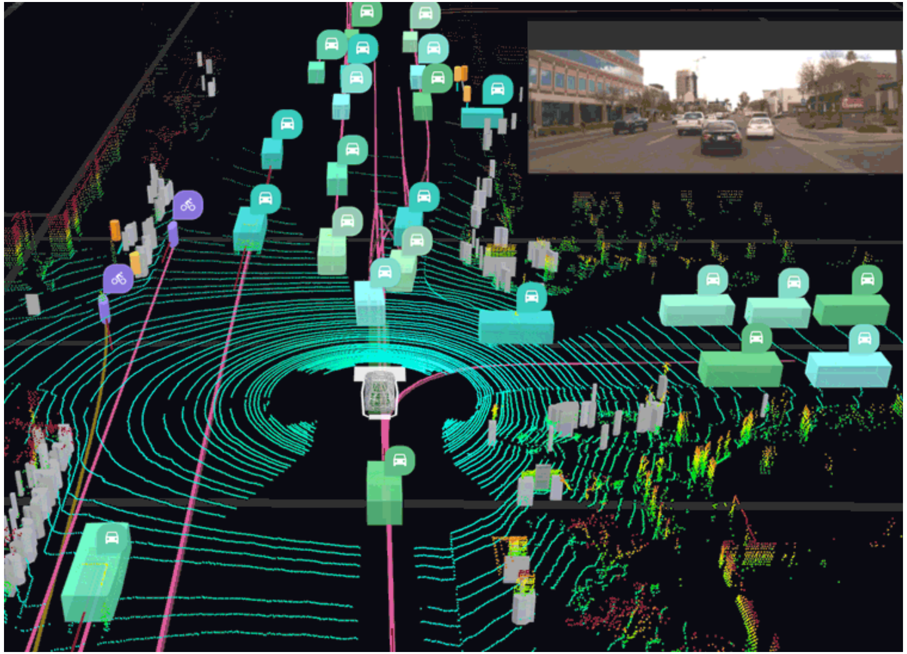


Drivability Map

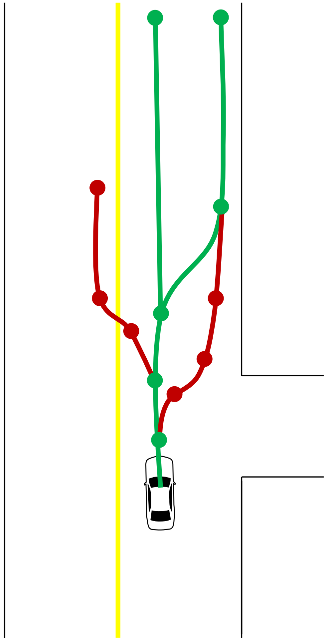
<u>Semantic Declarative Programming:</u>

Write a data stream fusion pipeline *<u>as a single query</u>*: **“Compute Drivability Map”?**

How???



Sensor data at different formats and modalities



Drivability Map

- A query compiler needs the reasoning capability to understand what “Drivability Map” is
- Which DNNs can consume camera, LiDARs and HD maps to detect objects/lanes to construct “Drivability Map”?
- How to connect data fusion operations to continuously compute “Drivability Map” ?

How to Fuse Semantic Stream Data?

1.Detecting objects

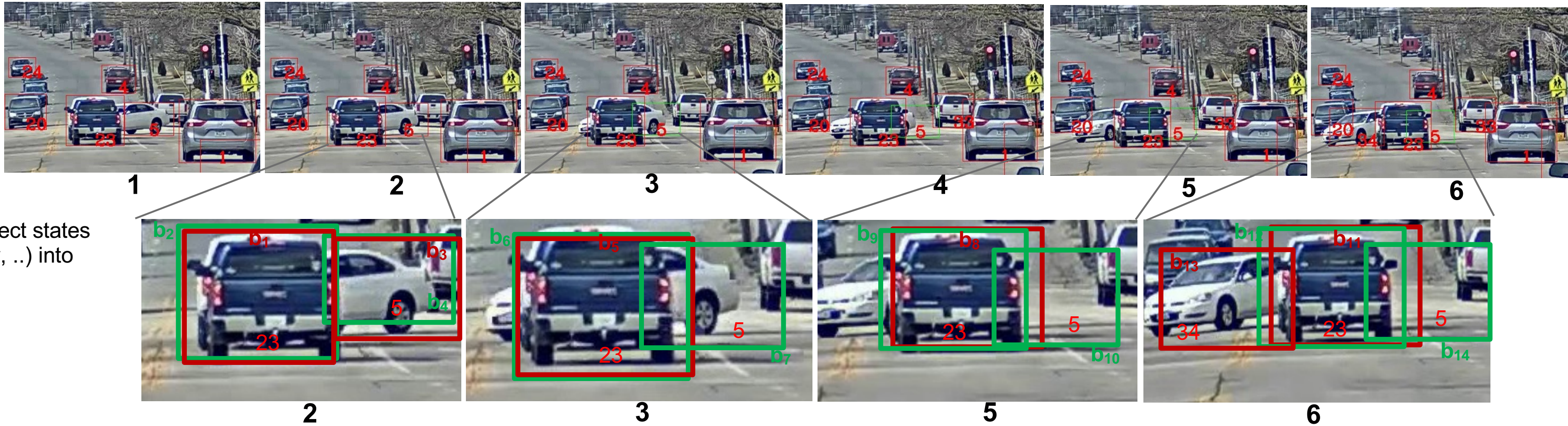
1 2 3 4 5 6

An example for multiple object tracking pipeline with Deep Neural Networks (DNNs)

How to Fuse Semantic Stream Data?

1.Detecting objects

2.Propagating object states (location, velocity, ..) into future frames



det($\mathbf{b_1}$,car,0.8), det($\mathbf{b_3}$,car,0.7), trk($\mathbf{b_2}$,23), trk($\mathbf{b_4}$,5),…

det($\mathbf{b_5}$,car,0.8), trk($\mathbf{b_6}$,23), trk($\mathbf{b_7}$,5),…

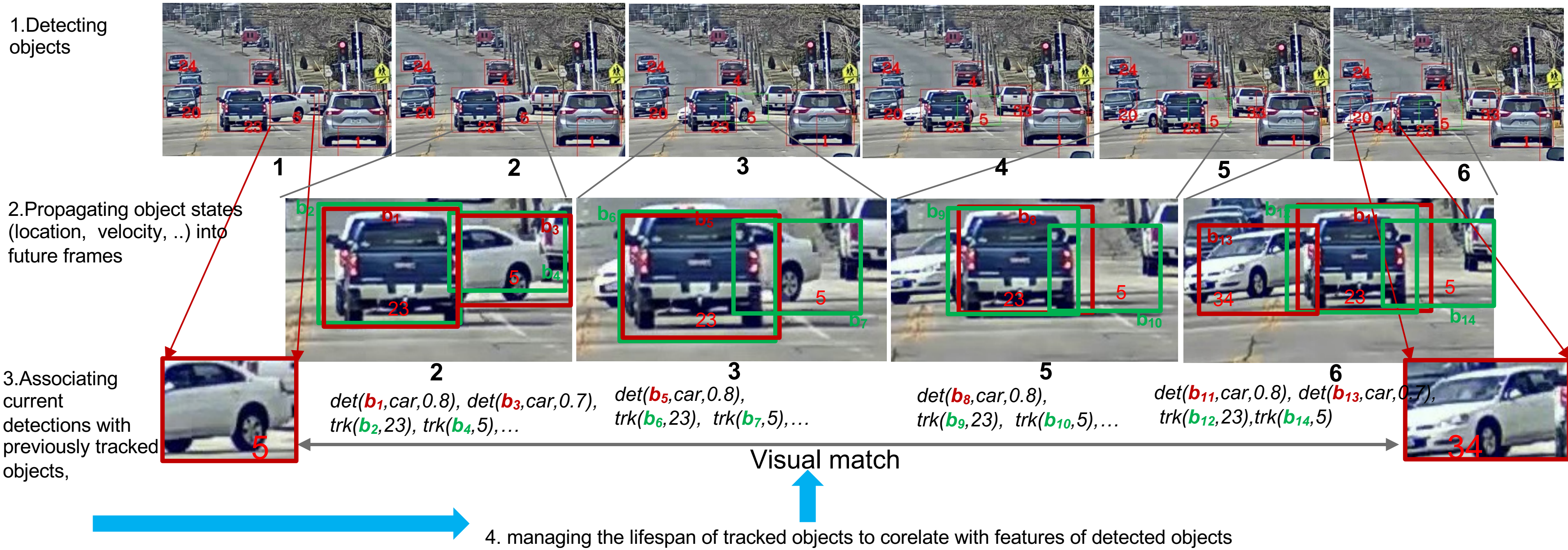
det($\mathbf{b_8}$,car,0.8), trk($\mathbf{b_9}$,23), trk($\mathbf{b_{10}}$,5),…

det($\mathbf{b_{11}}$,car,0.8), det($\mathbf{b_{13}}$,car,0.7), trk($\mathbf{b_{12}}$,23),trk($\mathbf{b_{14}}$,5)

Stream of semantic symbols

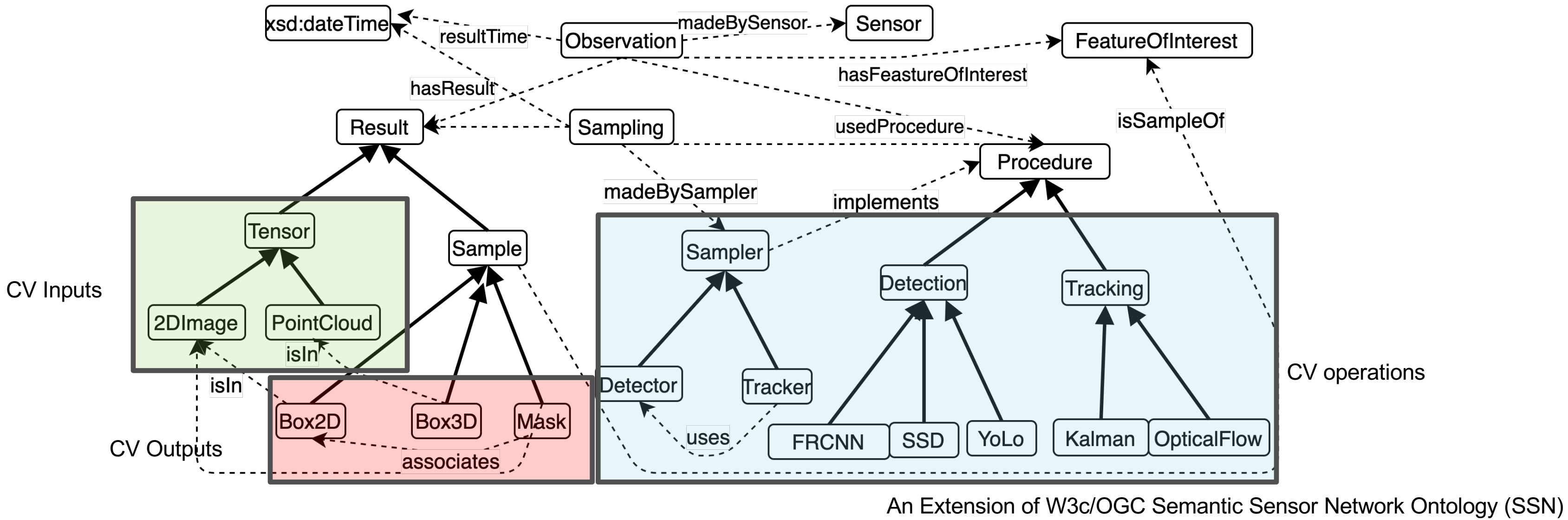
An example for multiple object tracking (MOT) pipeline with Deep Neural Networks

How to Fuse Semantic Stream Data?



Streams of semantic symbols ⇒ use rules to represent <u>association hypotheses</u> ⇒ Reasoning

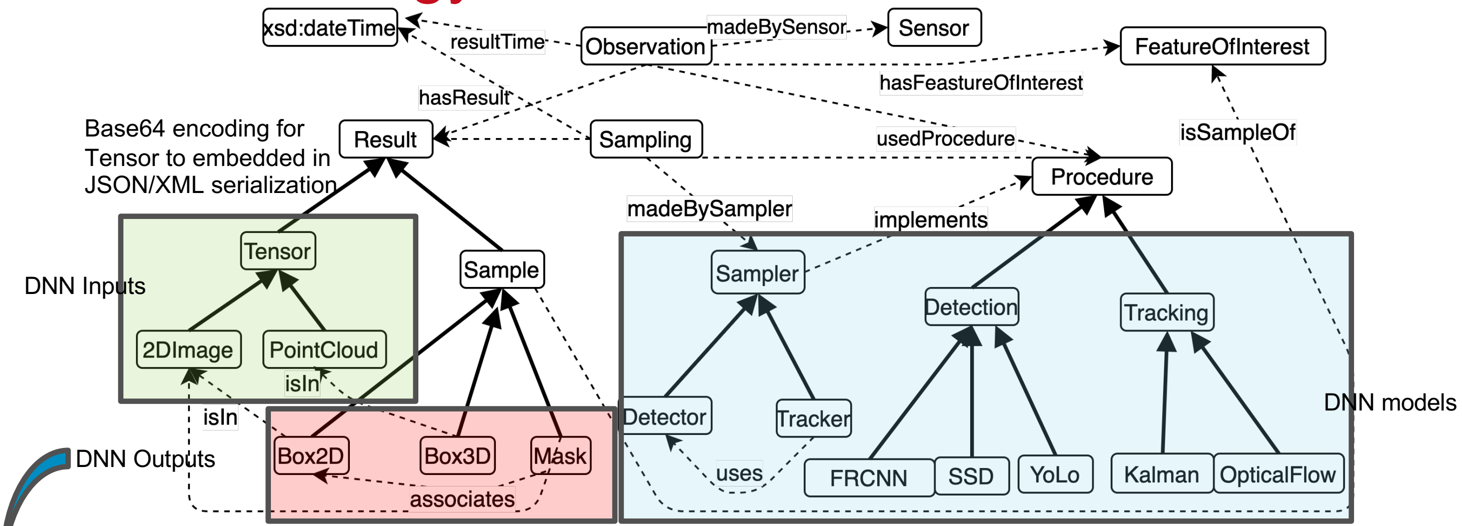
Ontology for Semantic Stream Fusion



- An abstraction of DNNs as Sensors or Samplers
- Unify inputs/outputs of Sensors and DNNs →seamless integration of sub-symbolic with symbolic

Schneider P., .., Le-Phuoc D.: Stream Reasoning Playground. ESWC 2022

Ontology for Semantic Stream Fusion




```
// time point/frame 2
<<:det1 :det :b1>> a :car; :hasConfScore 0.8; sosa:resultTime 2.
<<:det3 :det :b3>> a :car; :hasConfScore 0.7; sosa:resultTime 2.
<<:trk23 :trk :b2>> sosa:resultTime 2.
<<:trk5 :trk :b4>> sosa:resultTime 2.
// time point/frame 3
<<:det5 :det :b5>> a :car; :hasConfScore 0.8; sosa:resultTime 3.
<<:trk23 :trk :b6>> sosa:resultTime 3.
<<:trk5 :trk :b7>> sosa:resultTime 3.
```

Semantic Stream in Standardized Data Format

RDF* (W3C RDF-star and SPARQL-star)

Haler A., Le-Phuoc D. … The modular SSN ontology: A joint W3C and OGC standard specifying the semantics of sensors, observations, sampling, and actuation. Semantic Web 10(1): 9-32 (2019)

Janowicz K., …Le-Phuoc D., ..: SOSA: A lightweight ontology for sensors, observations, samples, and actuators. J. Web Semant. 56: 1-10 (2019)

Semantic Stream Reasoning Program

- Semantic Reasoning Program $\mathbf{\Pi}$ is **<u>a set of weighted rules</u>** $\boldsymbol{r}$ in the form: $\boldsymbol{\omega} : \boldsymbol{\alpha} \leftarrow \boldsymbol{\beta}$
  - α, β are ***logic/symbolic formulas*** (Answer Set Programming program with *<u>sliding windows,</u>* i.e. LARS program) and $\omega \in \mathbb{R} \cup \{x\}$ is the weight of the rule
  - If $\omega = x$, then r is a ***<u>hard rule</u>***, otherwise r is a ***<u>soft rule</u>***
- The semantics of $\mathbf{\Pi}$ is given by
  - the answer streams of $\mathbf{S}$ the LARS program $\mathbf{\Pi_S}$ obtained from $\mathbf{\Pi}$ by dropping the weights
  - and for all r where $\mathbf{S}$ is violated $\alpha \leftarrow \beta \Longrightarrow \mathbf{S}$ gets a probability $\boldsymbol{Pr_{\Pi}(S)}$ calculated from the weights of the rules retained for $\mathbf{\Pi_S}$ following **Markov Logic Network**

Le-Phuoc D. et al. A Scalable Reasoning and Learning Approach for Neural-Symbolic Stream Fusion. AAAI 2021

A semantic reasoning program in ASP language

ASP: Answer Set Programing

hard-rules.ssr

```
//hard rule 1: object enters the FoV-> trigger EC axioms
initiates(enters(O),inFoV(O),T):-enters(O)@T

//hard rule 2: object leaves the FoV-> release EC axioms
terminates(leaves(O),inFoV(O),T):-leaves(O)@T

//hard rule 3: transitive rule between the tracklet and object
trklet(Trk,O)@T:-trk(Trk,B)@T,iSO(B,O).
//hard rule 4: transitive rules between the tracklet and object
iSO(B2,O):-iSO(B1,O),trk(Trk,B1),trk(Trk,B2),B1!=B2.

//hard rule 5: constraint on 1 object with only 1 tracklet
:~trklet(T1,O),trklet(T2,O),T1!=T2.

//hard rule 6: trigger EC trajectory axiom
trajectory(trklet(Trk1,O1),T1,trklet(Trk2,O2),T2):-T=T1+T2,
ends(Trk1)@T, starts(Trk2) @ T, starts(Trk1) @ T1.

//hard rule 7: trigger EC antitrajectory axiom
antiTrajectory(trklet(Trk,O),T1,occl(O),T2:-occl(O)@T,
not trklet(Trk,O)@T, T=T1+T,T2>0

//hard rule 8: trigger EC antitrajectory axiom
antiTrajectory(occl(O),T1,trklet(Ttr,O),T2):-trklet(Trk,O)@T,
T=T1+T2, T2>0
```

Hard rules are traditional logic rules

soft-rules.ssr

```
//soft rule 1: detect vehicles entering FoV
enters(O)@T :- det(B,car,S),iSO(B,O), not inFoV(O)[5 sec], S>=0.8.

//soft rule 2: detect vehicles leaving FoV
leaves(O)@T:-not det(B,car,S)@T[5 sec], iSO(B,O),
not inFoV(O)[5 sec], S>=0.8.

//soft rule 3: emulate SORT algorithm
iSO(B1,O) :- trk(T1,B1)@T, det(B2,OT,S) @ T,
trklet(T1,O), iou(B1,B2).

// soft rule 4: emulate DeepSORT algorithm
iSO(B1,O) :- trk(Trk1,B1) @ T, vMatch(B1,B2), iSO(B2,O),
trklet(Trk2,O), ends(Trk2)@Te, T<Te+3,
trk(Trk2,O2)@Te in [5 sec].

//soft rule 5: detect occlusion events
occl(O)@T1:-trk(Trk1,B1)@T2,trk(Trk2,B2),trklet(Trk1,O)@T2,
Trk1!=Trk2,iou(B1,B2), ends(Trk1)@T1,T1=T2+1.
```

All soft rules will be learnt to assign weights

Hard rules as knowledge-driven constraints

- Common Sense knowledge
  - Event Calculus :
    - Axioms to enforce the Law of inertia
    - Axioms on Trajectory, cause and effects, etc
  - Spatial and temporal reasoning rules: RCC-5, RCC-8, etc
- Domain-specific knowledge
  - Object motion constraints and patterns
  - Optical laws, e.g. optical flow
  - **Expert Knowledge embedded in Objects, Buildings and Roads**

Soft rules as association hypotheses (if-then rules)

$$\omega : \alpha \leftarrow \beta$$

weight to be learnt

The rule to trigger the event "a car enters *the Field of View of a camera"*

$$30 : @_T enters(O) \leftarrow @_T det(B, car, S), iSO(B, O), not \boxplus^5 \Diamond inFoV(O), S >= 0.8$$

- det (B,car,S) → a detected car at bounding box B with a confidence score S
- iSO(B,O): a bounding box B is a sample of object O (sosa:isSampleOf)
- inFoV(O): object O is in the Field of View

logic rule with *sliding windows*

```
//soft rule 1: detect vehicles entering FoV
enters(O)@T :- det(B,car,S),iSO(B,O), not inFoV(O)[5 sec], S>=0.8.
```

Rule Language of Answer Set Programming

CQELS-RL rules : SHACL+ SPARQL-star +sliding windows

```
//soft rule 1: detect vehicles entering FoV
ssr:rule_w_1 a sh:NodeShape;
sh:rule [
  a sh:CQELSRule ;
  sh:prefixes ssr: ;
  sh:construct """
    CONSTRUCT {<<?O :enters <ssr:FoV>> @ ?T.}
    WHERE {
      STREAM <:ssr> {
        <<?Dt :det ?B >>@ ?T; :hasConfScore ?S.
        ?B sosa:isSampleOf ?O ; a :car.
        FILTER (?S > 0.8)
      }
      NAF STREAM <:ssr> window[5 sec] {
          ?O :inFOV ssr:FoV.
      }
    }
```

A semantic reasoning program in CQELS-RL

```
//soft rule 1: detect vehicles entering FoV
```
[redacted]

```
//soft rule 2: detect vehicles leaving FoV
```
[redacted]

```
//soft rule 3: emulate SORT algorithm
```
[redacted]

```
//soft rule 4: emulate DeepSORT algorithm
```
[redacted]

Syntaxes and rules are long and error-prone

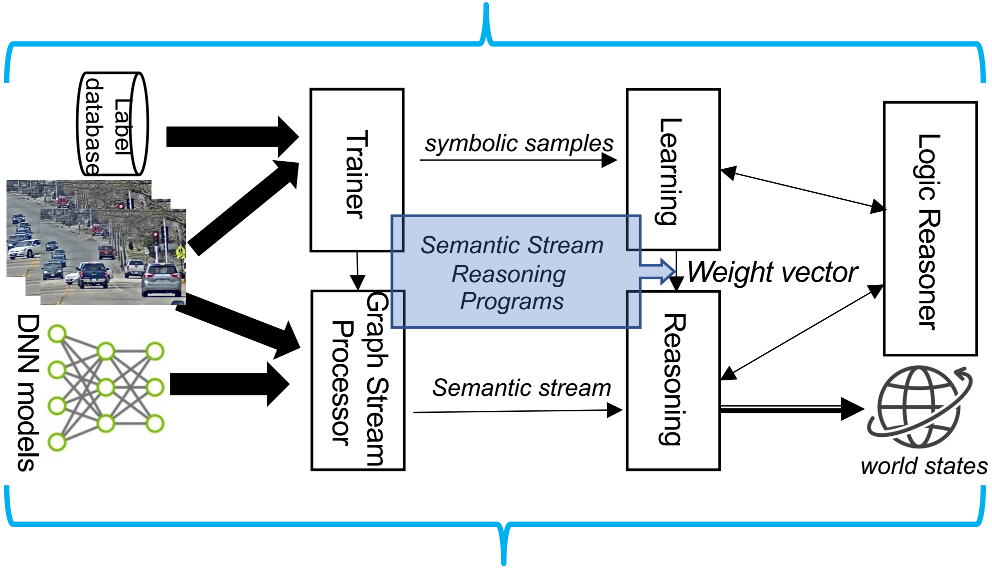
Can we automate it?

Use language model+ Semantic graphs

Reasoning program integrates both SORT and DeepSORT for Multi Object Tracking across Mutiple Cameras

Semantic Stream Reasoning Framework

Learning phase: set weights based on labelled stream → scalable learning algorithms



Execution phase: continuously execute the reasoning algorithm on reasoning programs with learnt weights → incremental reasoning algorithms

Le-Phuoc D. et al. A Scalable Reasoning and Learning Approach for Neural-Symbolic Stream Fusion. AAAI 2021

Nguyen D. M…Le-Phuoc D. Towards autonomous semantic stream fusion for distributed video streams. DEBS 2021

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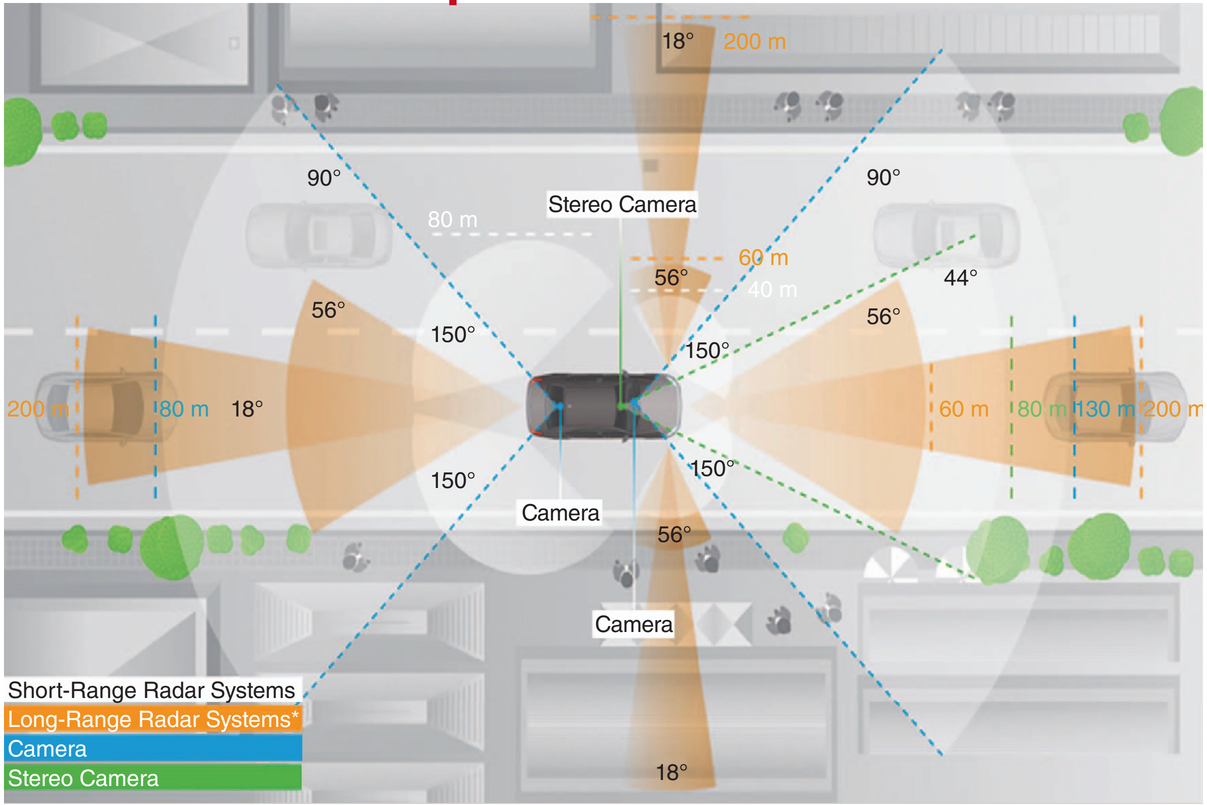
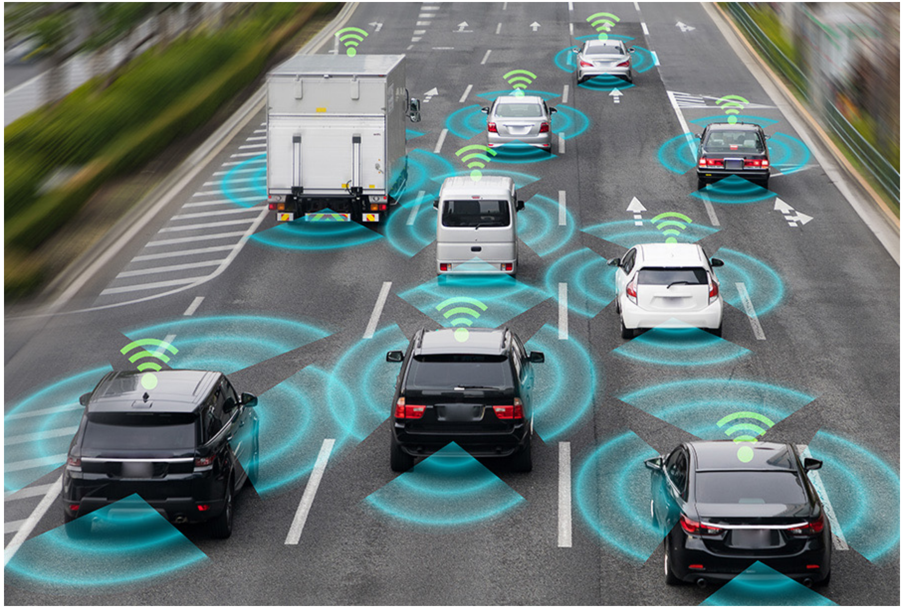
Perception of Ego-Vehicle:
In-Vehicle sensors provide limited view of the world



Mercedes-Benz S-Class S 500 INTELLIGENT DRIVE

Julius Ziegler et al Making Bertha Drive—An Autonomous Journey on a Historic Route, IEEE Intelligent Transportation Systems Magazine (Volume: 6, Issue: 2, Summer 2014)

Cooperative Perception for ADAS and ITS : V2X and I2V



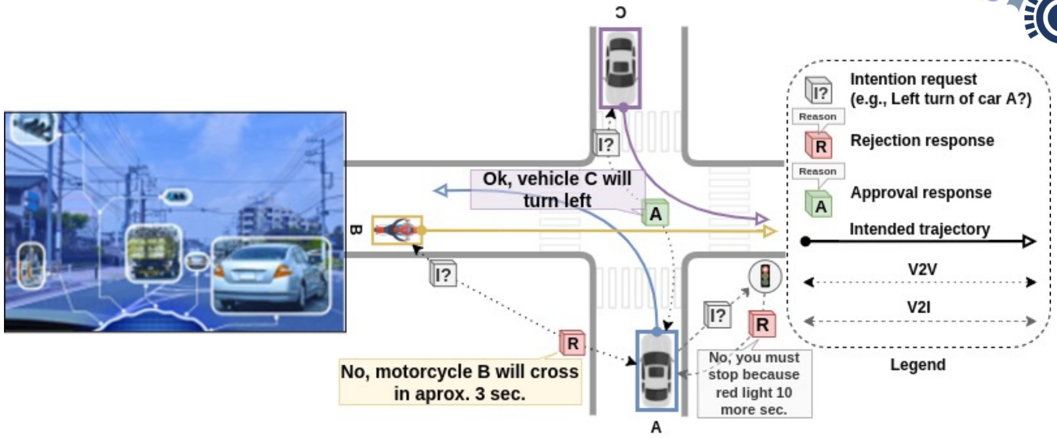
V2V: Vehicle to Vehicle

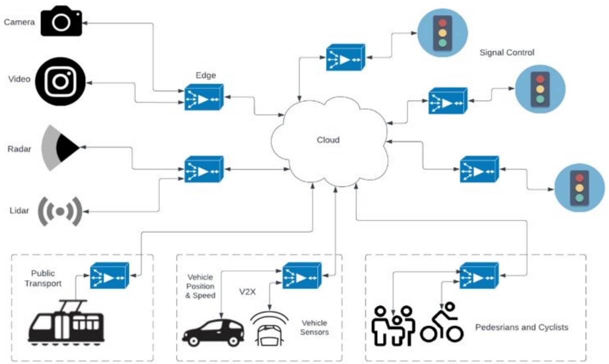
I2V: Infrastructure to Vehicle

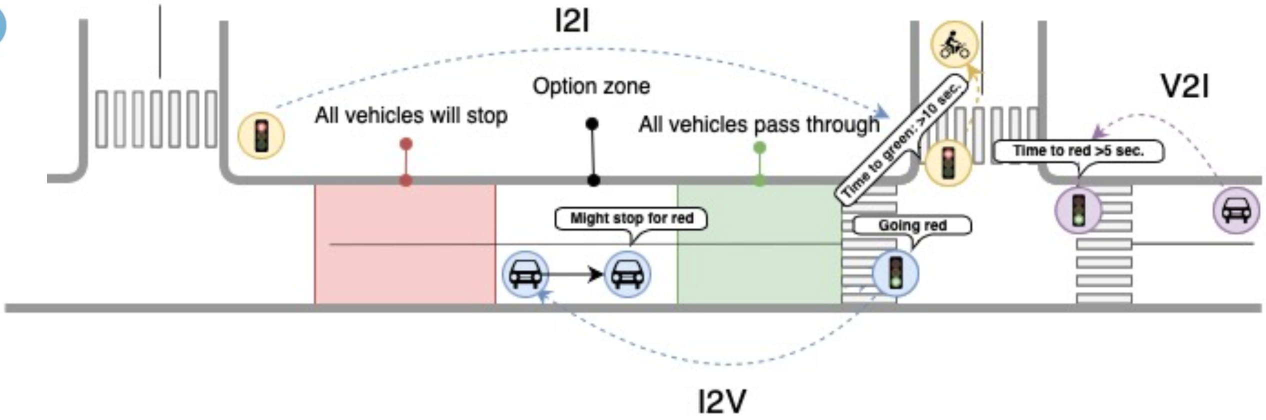
Distributed Semantic Streams for ADAS and ITS : V2X, I2I and I2V

Enhance Vehicle's Perception with V2I data streams

- Intersection Movement Assist with explainable messages
- Participants send intentions and get data-supported feedback that explains the reason why they are either approved or rejected. For example, Car A intends to turn left while Motorcycle B has the priority



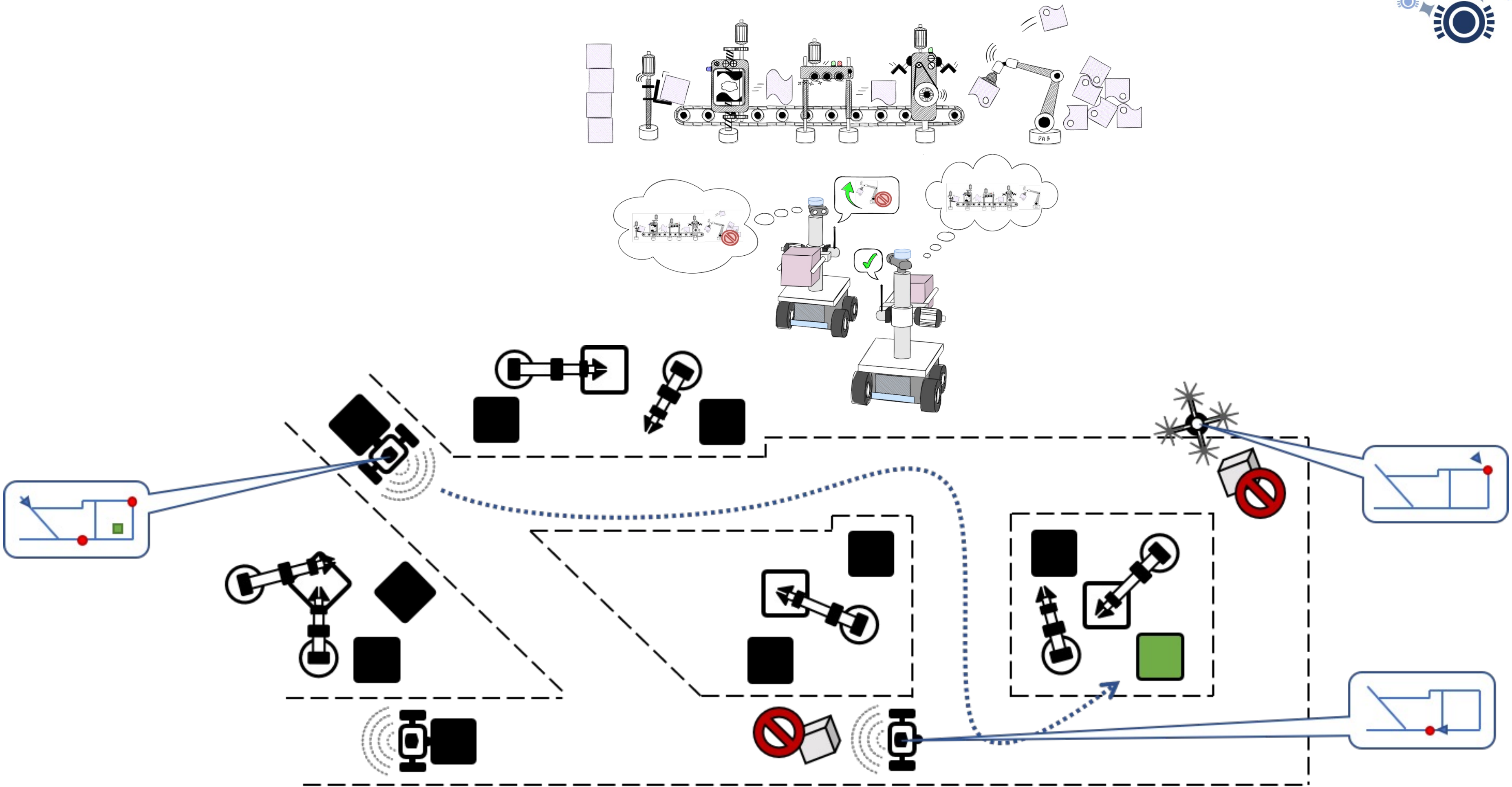




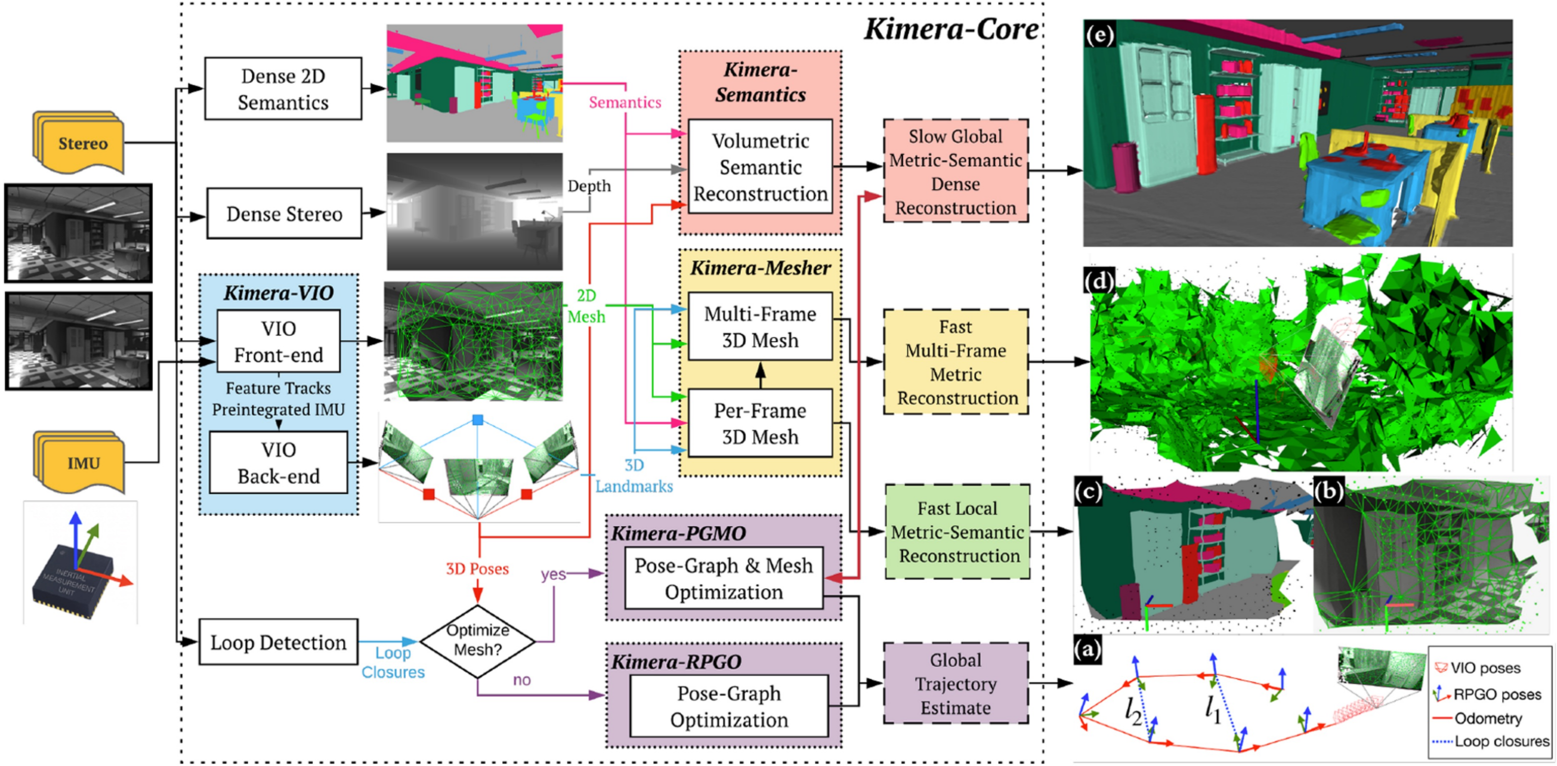
Enhance Intersection's Perception with I2I and I2V data streams

- Active option zone protection system based on swarm

Smart Factories with Intelligent Mobile Robots

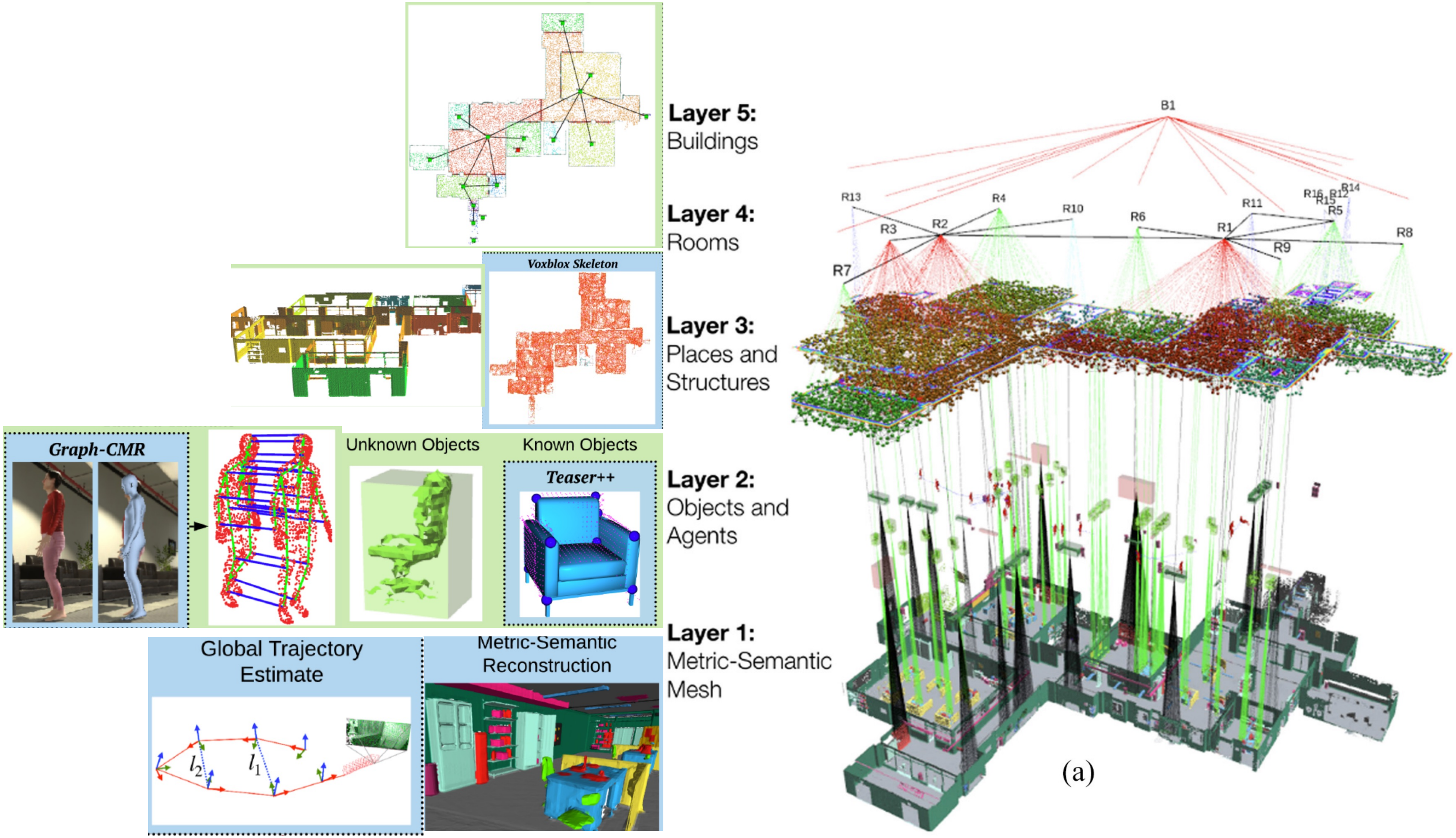


Integrate SLAM Components to Build Semantic Streams in ROS



Rosinol A, Violette A, Abate M, et al. Kimera: From SLAM to spatial perception with 3D dynamic scene graphs. *The International Journal of Robotics Research*. 2021

Fuse Different Semantic Abstraction Levels of Semantic SLAM



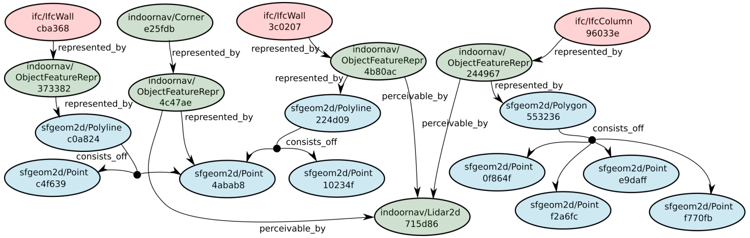
Connect Sensors to Stream Graphs

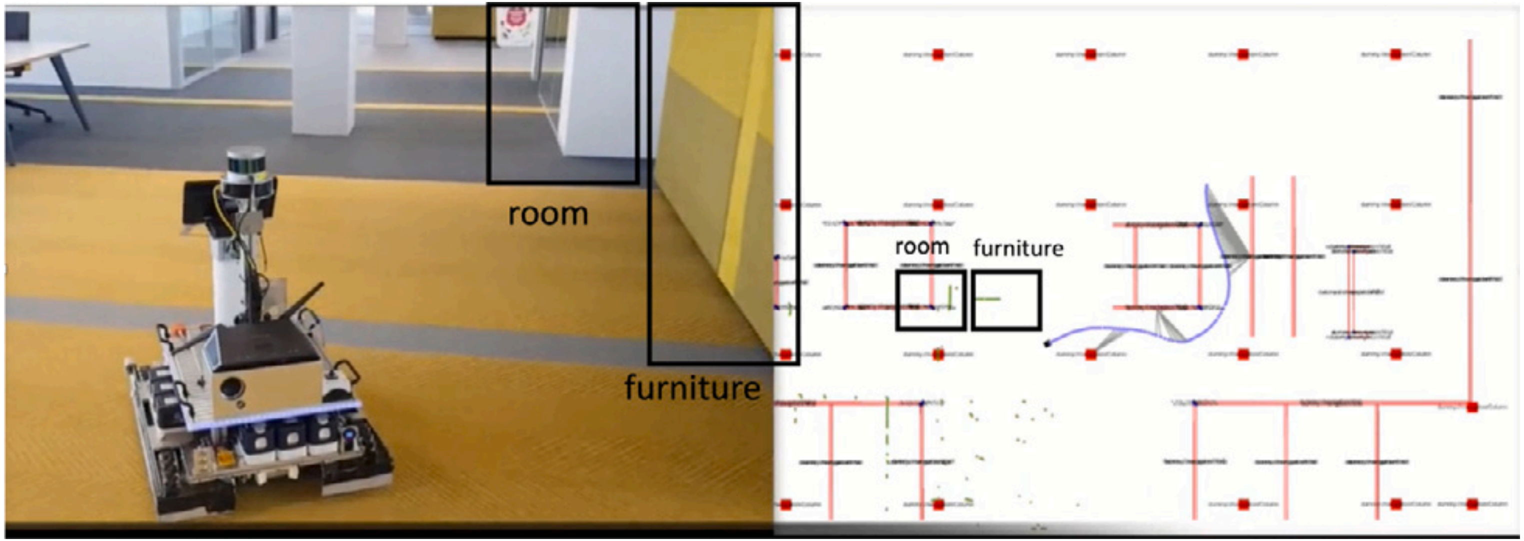
Program Semantic-based Perception

Emerging Applications

Integrate Spatial Knowledge into Perception

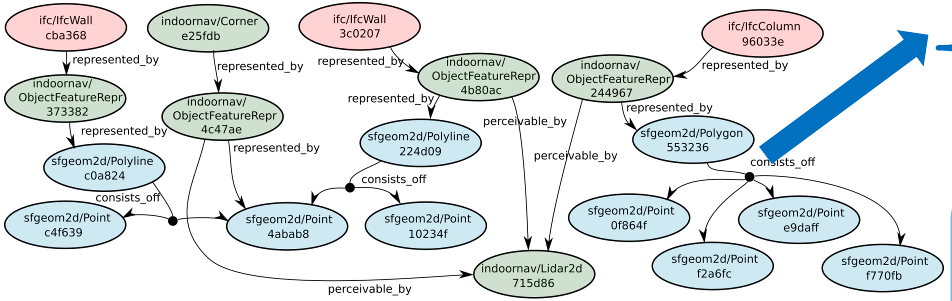
Semantic SLAM can use Semantic Building Information

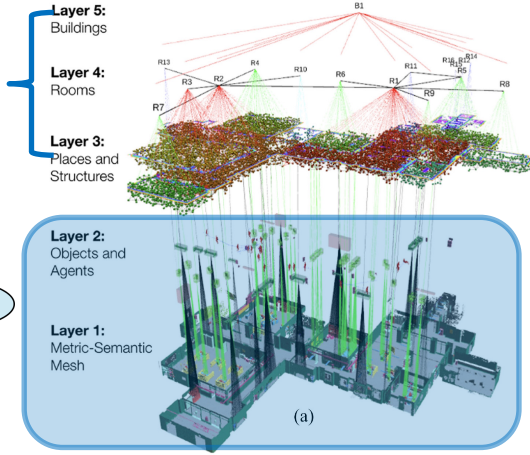


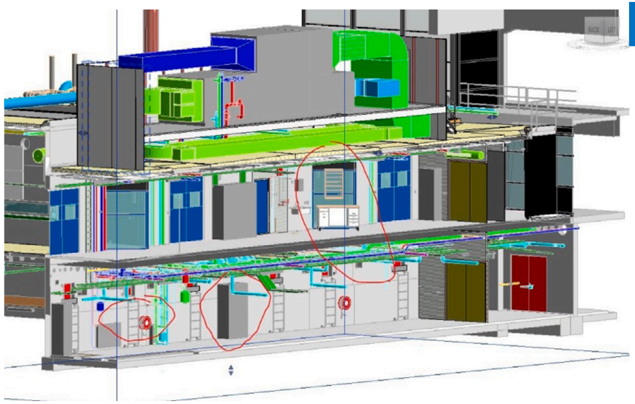


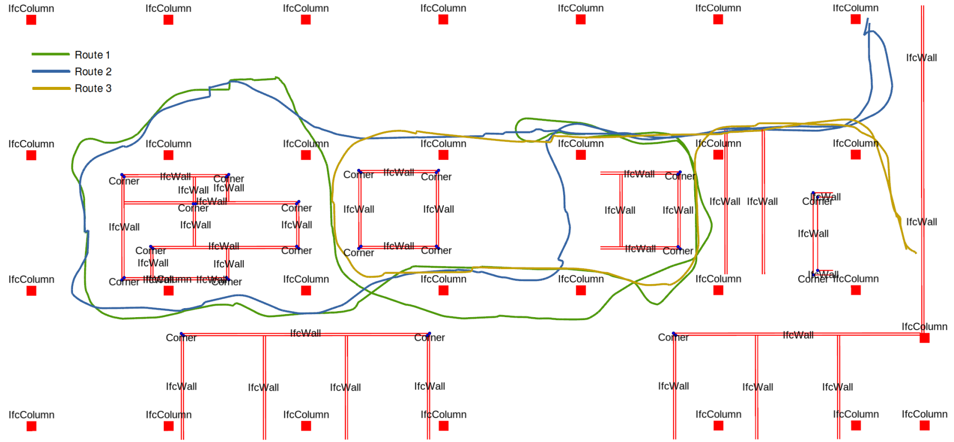
R. W. M. Hendrikx, Pieter Pauwels, Elena Torta, Herman P. J. Bruyninckx, M. J. G. van de Molengraft: Connecting Semantic Building Information Models and Robotics: An application to 2D LiDAR-based localization. ICRA 2021

Semantic SLAM can use Semantic Building Information









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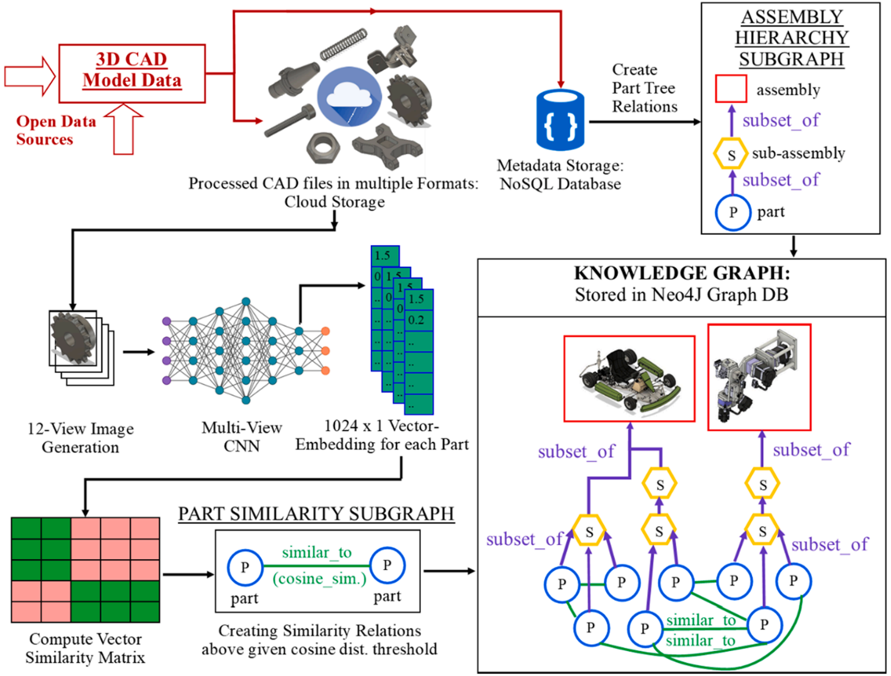

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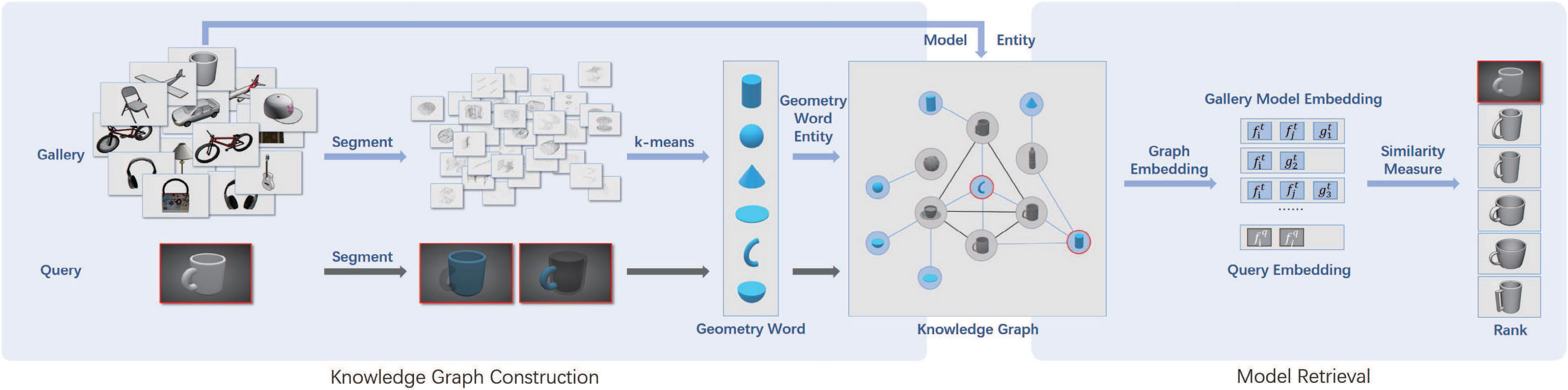

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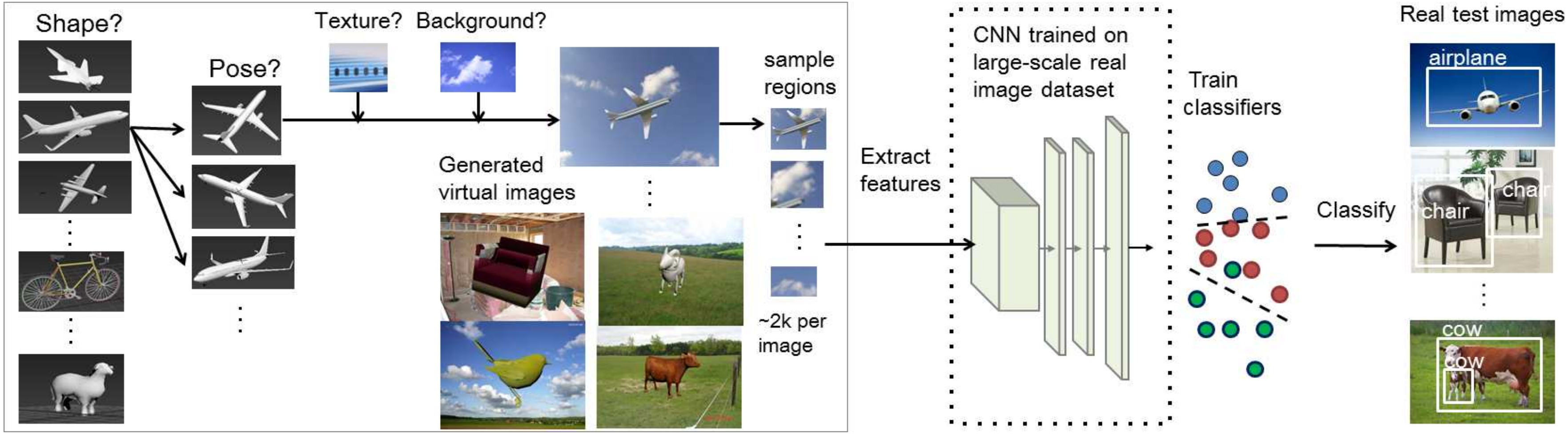
3D CAD models as Priors for training 3D object detectors



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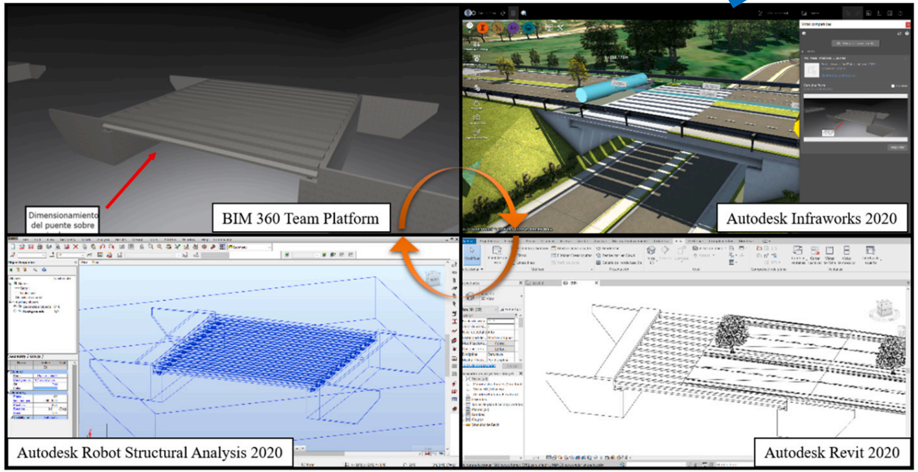

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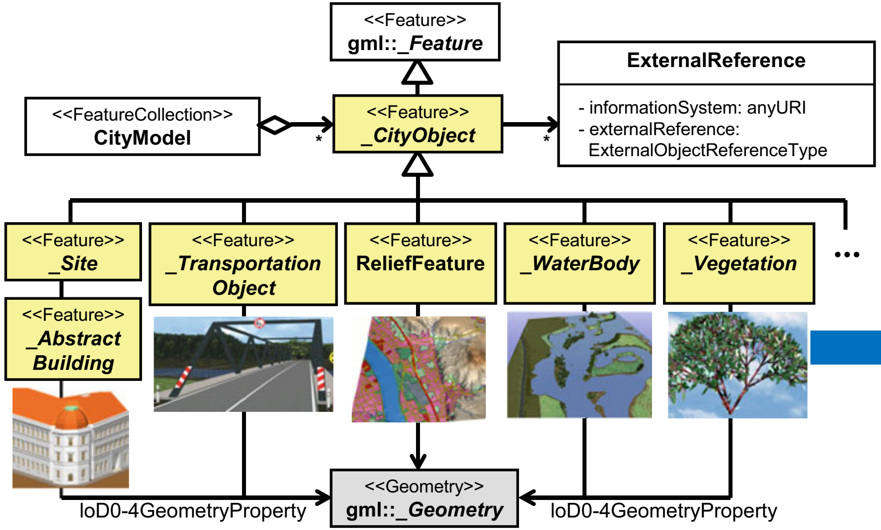
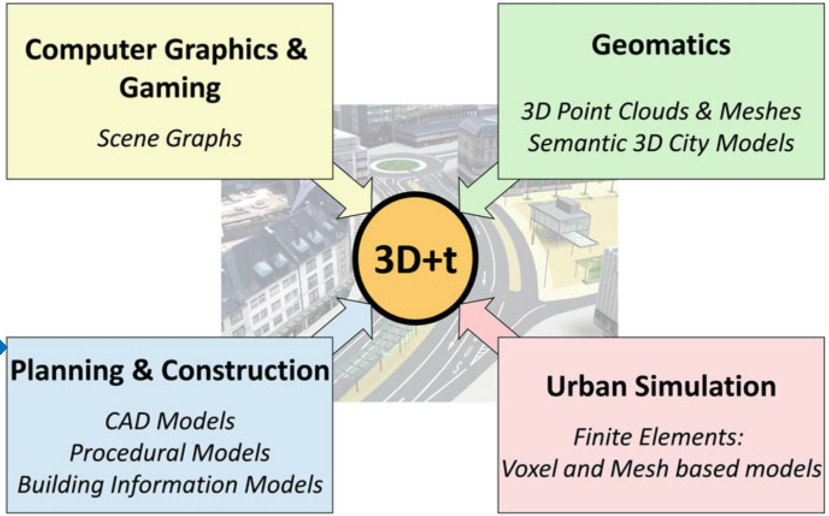
And Semantic City Models?



CityGML with Open 3D city models: https://www.3dcitydb.org/



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Can Spatial Knowledge be used to build better Perception Systems?

Beyond Large Language Models !!!

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